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Energy Procedia 50 (2014) 893 – 906
Energy Procedia

The International Conference on Technologies and Materials for Renewable Energy, Environment and Sustainability, TMREES14

A New Approach ACO for Solving the Compromise Economic and Emission with the Wind Energy

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Abstract

Environmental legislation, with its increasing pressure on the energy sector to control greenhouse gases, is a driving force to reduce CO2 emissions, forced the power system operators to consider the emission problem as a consequential matter beside the economic problems, so the economic power dispatch problem has become a multi-objective optimization problem. This paper sets up an new algorithm , ant colony optimization (ACO), to solve the optimization with combined economic emission dispatch. This problem has been formulated as a multi-objective problem by considering economy, emission and wind energy simultaneously. The feasibility of the proposed approach was tested on 3-unit and 15-unit systems. The simulation results show that the proposed algorithm gives comparatively better operational fuel cost and emission in less computational time compared to other optimization techniques.

Selection and peer-review under responsibility of the Euro-Mediterranean Institute for Sustainable Development (EUMISD)

Keywords: Economic Power Dispatch (EPD); Ant Colony Optimization (ACO);Wind Energy.

1. Introduction

The success of any stochastic search method heavily depends on striking an optimal balance between exploration and exploitation. These two issues are conflicting but very crucial for all the metaheuristic algorithms. Exploitation is to effectively use the good solutions found in the past search whereas exploration is expanding the search to the unexplored areas of the search space for promising solutions. The reinforcement of the pheromone trail by the

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Selection and peer-review under responsibility of the Euro-Mediterranean Institute for Sustainable Development (EUMISD)
doi:10.1016/j.egypro.2014.06.108

artificial ants exploits the good solution found in the past. However, excessive reinforcement may lead to premature convergence. Many metaheuristic or optimization algorithms need some parameters to be set in order to obtain good solutions. Usually, those values are 'calculated' in an empirical (or heuristical) way. But this method is time consuming and it is not falling on the good values of the parameters.

Our work contributes to this problem by applying another metaheuristic method. The Ant Colony Optimization (ACO). to validate our work we use to solve the problem of multi-objective optimization; the problem consists in combining the economic control system and the gas emission with the production of electrical energy and the wind energy.

The problem which has received much attention. It is of current interest of many utilities and it has been marked as one of the most operational needs. In traditional economic dispatch, the operating cost is reduced by the suitable attribution of the quantity of power to be produced by different generating units. However the optimal production cost can not be the best in terms of the environmental criteria. Recently many countries throughout the world have concentrated on the reduction of the quantity of pollutants from fossil fuel to the production of electrical energy of each unit. The gaseous pollutants emitted by the power stations cause harmful effects with the human beings and the environment like the sulphur dioxide (SO2), nitrogen oxide (NOx) and the carbon dioxide (CO2), etc. Thus, the optimization of production cost should not be the only objective but the reduction of emission must also be taken into account. Considering the difference in homogeneity of the two equations, the equation of the cost of fuel given in $/hr, and the equation of emission of gases to the production of electrical energy given in Kg/hr.

This method was tested on 3-unit and 15-unit systems. The algorithm was developed MATLAB environment programming.

The proposed approach results have been compared to those that reported in the literature recently. The results are promising and show the effectiveness and robustness of the proposed.

2. Economic Power Dispatch Formulation

2.1. Problem formulation

2.1.1. Minimization of Fuel Cost

The power balance constraint and the generating power constraints for all units should be satisfied. In other words [2], the EPD problem is to find the optimal combination of power generations which minimize the total fuel cost while satisfying the power balance equality constraint and several inequality constraints on the system [3].

The total fuel cost function is formulated as follows [4]:

$$f(P_G) = \sum_{i=1}^{NG} f_i(P_{Gi}) \tag{1}$$

$$f_i(P_{Gi}) = a_i P_{Gi}^2 + b_i P_{Gi} + c_i \tag{2}$$

Where $f(P_G)$,is the total production cost ($/h).

$f_i(P_{Gi})$ is the fuel cost function of unit i in $/h;

P_{Gi} is the real power output of unit i in MW; a_i, b_i, c_i the cost coefficients of the i th generator.

2.1.2. Non-smooth power economic dispatch

The fuel function is roughly expressed like quadratic function for each unit of generation in convex economic problems. This case involves to bring closer calculation and the results in a solution erroneous, consequently. So of various types of physical and operational constraints are added in the problem for the correction of the optimal solution, the problem transforms itself into problem of forced optimization nonlinear. Economic dispatch problem with the effect of point of valve is one of these problems, which is classified like nonconvex problem and it is very difficult to find an optimal solution to him .

The inclusion of the effect of point of valve in the cost of fuel of the unit of generation provides a more suitable representation compared to the cost of fuel. While the point of valve is finalized with rises, the performance of fuel function includes a higher nonlinear series. For this reason, as for the study aimed at considering the effects of point of valve, a nonconvex function is used

In reality, the objective function has non differentiable points according to valve point loading effects. Therefore, the objective function should be composed of a set of non-smooth cost functions.

Multi-valve steam turbines based generating units are characterized by complex non-linear fuel cost function. The dotted line in the figure. 1 is the variation of the performance cost function taking into account the valve effects. To take account for the valve-point effects, sinusoidal terms are added to the quadratic cost functions as follows:

$$f(P_G) = \sum_{i=1}^{Ng}\left(a_i P_{Gi}^2 + b_i P_{Gi} + c_i + \left|d_i \times \sin\left\{e_i \times \left(P_i^{\min} - P_i\right)\right\}\right|\right) \tag{3}$$

Where d_i, e_i are the cost coefficients for ith generator reflecting valve-point effects.

2.2. Minimization of total emission and fuel cost

The most important emissions considered in the power generation industry due to their effects on the environment are sulfur dioxide (SO_2) and nitrogen oxides (NO_x) [5]. These emissions can be modeled through functions that associate emissions with power production for each unit. One approach to represent SO_2 and NO_x emissions is to use a combination of polynomial and exponential terms [6]:

$$EC(Pg) = \sum\left(\alpha_i P_{gi}^2 + \beta_i P_{gi} + \gamma_i\right) + \varepsilon_i \exp\left(\lambda_i P_{gi}\right) \tag{4}$$

where

α_i , β_i , γ_i , ε_i and λ_i are coefficients of the ith generator emission characteristics..

The bi-objective combined economic emission dispatch problem is converted into single optimization problem by introducing price penalty factor h as follows.

Minimise $F = FC + h * EC$

Subjected to the power flow constraints of equations. The price penalty factor h blends the emission with fuel cost and F is the total operating cost in \$/h.The price penalty factor hi is the ratio between the maximum fuel cost and maximum emssion of corresponding generator [7].

$$h_i = \frac{FC(P_{gi}^{\max})}{EC(P_{gi}^{\max})}$$

The following steps are used to find the price penalty factor for a particular load demand

1. Find the ratio between maximum fuel cost and maximum emission of each generator.

2. Arrange the values of price penalty factor in ascending order.

3. Add the maximum capacity of each unit $P_{gi}^{\max}$ one at a time, starting from the Smallest hi unit until $\sum P_{gi}^{\max} \geq P_d$

4. At this stage, hi associated with the last unit in the process is the price penalty factor h for the given load.

The above procedure gives the approximate value of price penalty factor computation for the corresponding load demand. Hence a modified price penalty factor (hm) is introduced in this work to give the exact value for the particular load demand. The first two steps of h computation remain the same for the calculation of modified price penalty factor. Then it is calculated by interpolating the values of hi corresponding to their load demand values.

2.3. Problem Constraints

2.3.1. Active Power Balance Equation

For power balance an equality constraint should be satisfied. The generated power should be the same as total load demand added to the total line losses. It is represented as follows:

$$\sum_{i=1}^{NG} P_{Gi} = \sum_{j=1}^{ND} P_{Dj} + P_L \tag{5}$$

$\sum_{j=1}^{ND} P_{Dj}$ is the total system demand;

$\sum_{i=1}^{NG} P_{Gi}$ is the total system production;

P_L is the total transmission loss of the system in MW;

NG is the number of generator units in the system;

ND is number of loads.

2.3.2. Active Power Generation Limits

Generation power of each generator should be laid between maximum and minimum limits. There are following inequality constraints for each generator

$$P_{Gi}^{\min} \leq P_{Gi} \leq P_{Gi}^{\max} \tag{6}$$

$P_{Gi}^{\min}, P_{Gi}^{\max}$ are the minimum and maximum generation limits of the real power of unit *i*.

3. Ant Colony Optimization

As shown in Figure 1, two ants start from their nest in search of food source at the same time to different directions. One of them chooses the path that turns out to be shorter while the other takes the longer sojourn. The ant moving in the shorter path returns to the nest earlier and the pheromone deposited in this path is obviously more than what is deposited in the longer path. Other ants in the nest thus have high probability of following the shorter route.

Colony Optimization is another powerful technique to solve hard combinatorial optimization problems. In ACO algorithms a finite number of artificial ants work together to search for the best solutions to the optimization problem under consideration. Each ant builds a solution and exchanges its information with other ants indirectly [8]. Although each ant can build a solution, high quality solutions are only found with this cooperation and information exchange [9].

In ACO algorithms a structural neighbourhood is defined for the given problem. Each ant builds a solution by moving in a sequence trough out the neighbourhood architecture. While building a solution each ant uses two different information sources.

The first source is private information which is the local memory of an ant and the second source is the publicly available pheromone trail together with problem specific heuristic information [10].

To build a feasible solution ants keep a tabulated list to keep the previously visited nodes. Publicly available pheromone trail provides knowledge about the decisions of ants from the beginning of the search process. An ant-decision table defined with the functional combination of this pheromone trail and problem specific heuristic values is used to direct the search. Pheromone evaporation strategies are used to avoid stagnation due to large accumulations [11].

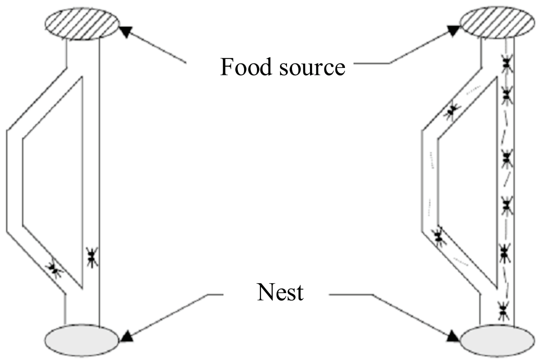

Fig. 1. Movement of ant algorithm

3.1. Solution Construction

Is where the artificial ants construct their solutions. This procedure implements a stochastic transition policy which is a function of pheromone trail. It controls the ants' moves to one of the adjacent states allowed in their vicinity by applying this policy. Once the ants have completed their solutions they calculate the quality of their solution, which will be used by the update pheromones procedure [12].

In ACO there are m artificial ants which are located at m random cities. Each ant applies a stochastic transition policy to decide on its next move.

Therefore, the probability that city j is selected by ant k to be visited after city i could be written as follows:

$$P_{ij}^k(t)=\begin{cases}\dfrac{[\tau_{ij}]^\alpha\cdot[\eta_{ij}]^\beta}{\sum_{l\in N_i^k}[\tau_{il}(t)]^\alpha\cdot[\eta_{il}]^\beta} & if \quad j \in N_i^k\\ \end{cases} \tag{7}$$

In the above formula η_{ij} stands for the heuristic value specified according to the problem to be solved. In the Travelling Salesman Problem (TSP) case, η_{ij} is equal to $1/d_{ij}$.

N_i^k is the feasible neighbourhood of ant k at city i and τ_{ij} is the quantity of the pheromone on the path between the city i and j.

α and β are the parameters which is used to set the relative importance of the pheromone trail and the heuristic value. As α approaches 0 the pheromone trails become less important and the ants tend to choose the closest cities and the search becomes very much like a greedy search.

As β approaches 0 heuristic values are ignored and ants consider only the trails when deciding the path to follow. This leads to stagnation at the first good solutions found by the colony.

3.2. Pheromone Update

At the beginning m ants are placed to the n cities randomly. Then each ant decides the next city to be visited according to the probability P_{ij}^k given by Eq. (7). After n iterations of this process every ant completes a tour. Obviously, the ants with shorter tours should leave more pheromone than those with longer tours. Therefore the trail levels are updated as on a tour each ant leaves pheromone quantity given by $1/L^k$, where L^k the length of its tour respectively. On the other hand, the pheromone will evaporate as the time goes by. Then the updating rule of τ_{ij} could be written as follows:

$$\tau_{ij}(t+1)=\rho\cdot\tau_{ij}(t)+\Delta\tau_{ij} \tag{8}$$

$$\Delta\tau_{ij}=\sum_{k=1}^{m}\Delta\tau_{ij}^k\ ;$$

$$\Delta\tau_{ij}^k=\begin{cases}\dfrac{1}{L^k}, & \text{If edge(i, j) is solution of ant k,}\\ 0 & \text{otherwise}\end{cases} \tag{9}$$

Where t is the iteration counter, ρ Є [0, 1] the parameter to regulate the reduction of τ_{ij} the total increase of trail level on edge (i, j) and $\Delta\tau_{ij}$ k the increase of trail level on edge (i, j) caused by ant k, respectively.

After the pheromone trail updating process, the next iteration t + 1 will start.

1. Initialize:

Set time:=0 % is time counter

For every edge (i,j) set an initial value $\tau_{ij}(t)$=c for trail density and $\Delta\ \tau_{ij}$=0

2. Set t:=0 %s is travel step counter

For k:=1 to m do

Place ant k on a city randomly. Place the city in $visited_k$.

Place the group of the city in $tabu_k$.

3. Repeat until tabu list is full

Set t:=t + 1

For k:=1 to m do

Choose the next city to be visited according to the probability $P_{ij}^{k}(t)$ given by eq (7).

Insert the selected city in $visited_k$.

Insert the group of selected city in $tabu_k$.

4. For k:=1 to m do

Move the k-thant fromvisited$_k$(n) to visited$_k$(1).

Compute the tour length Lktraveled by the k-th ant.

Update the shortest tour found.

For every edge (i, j) do

For k:=1 to l do

Update the pheromone trail density τ_{ij} according to Eqs.

(8)– (9).

Time: =time + 1

5. If (time<TIME_MAX) then

Empty all visitedk and $tabu_k$

Goto Step 2.

Else

Print the shortest tour.

Stop

4. Simulation Results

The proposed ACO approach based on global and local search. is developed in the Matlab programming language using 7.04 version and tested on two networks:

4.1. Test system 1

The 3 generators test system [13] whose data are given below. The system demand is 850 MW; is considered as test system 1, the fuel and the emission coefficients including the limits of generation for the generators are presented in tables I, II and III.

The results obtained by the proposed algorithm are compared to those reported in the literature like Tabu search [14], NSGA-II [15], DE/BBO [16]. From the comparison, it is noticed that the proposed approach (ACO) gives reduction in fuel cost and the SO_2 emission and NO_x emission (Table IV). The convergence profiles of the best solution for the fuel cost and the SO_2 emission and NO_x emission are shown in Fig. 1, 2 and 3, respectively. It is noticed also from these figures that the convergence of the proposed approach (ACO) is promising , we got the results after only 30 iterations.

TABLE 1. FUEL COST COEFFICIENTS (3-UNIT SYSTEM)

Bus No	Power limit MW)		Cost Coefficients		
	$P_{Gi}^{\min}$	$P_{Gi}^{\max}$	a_i	b_i	c_i
1	150.0	600	0.001562	7.92	561.0
2	100	400	0.00194	7.85	310.0
3	50	200	0.00482	7.97	78.0

TABLE 2. SO_2 EMISSION COEFFICIENTS (3-UNIT SYSTEM)

Unit i	α_i	β_i	γ_i
1	1.6103e-6	0.00816466	0.5783298
2	2.1999e-6	0.00891174	0.3515338
3	5.4658e-6	0.00903782	0.0884504

TABLE 3. NO_X EMISSION COEFFICIENTS (3-UNIT SYSTEM)

	α_i	β_i	γ_i
1	1.4721848e-7	-9.4868099e-5	0.04373254
2	3.0207577e-7	-9.7252878e-5	0.055821713
3	1.9338531e-6	-3.5373734e-4	0.027731524

TABLE 4. COMPARISON OF TEST RESULTS OF 3-UNIT SYSTEM USING DIFFERENT METHODS FOR BI-OBJECTIVE.

Variable	DE/BBO [17]	NSGA-II [16]	Tabu [15]	Emission minimum ACO
PG1	435.1978	436.366	435.69	411.951833
PG2	299.9696	298.187	298.828	298.595129
PG5	130.6604	131.228	131.28	153.490052
cost ($/hr)	8344.58319	8344.651	8344.598	8342.952303
Emission SO_2(ton/h)	9.02194	9.02541	9.02146	8.983050
Emission NO_x (ton/h)	0.098686	0.098922	0.09863	0.088011
P_L(MW)	15.8289	15.781	15.798	14.0370
T (s)	/	/	/	0.62500

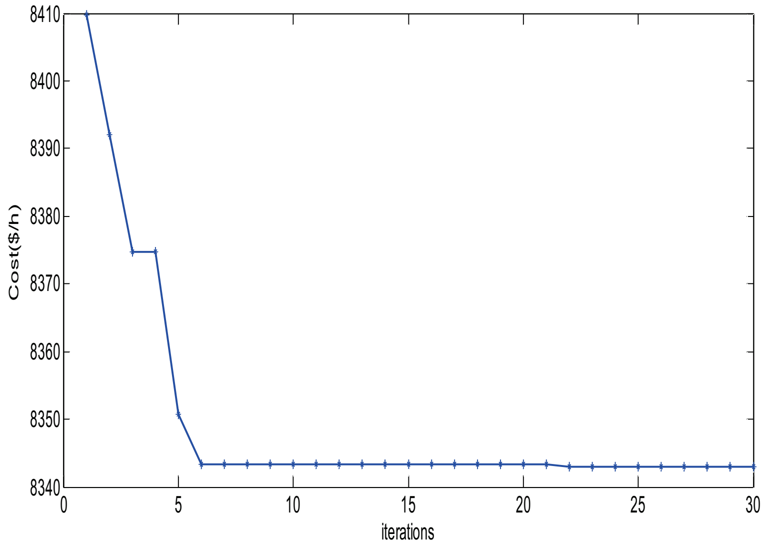

Fig. 2. Convergence characteristic for fuel cost minimization (3-unit system, demand 850 MW) .

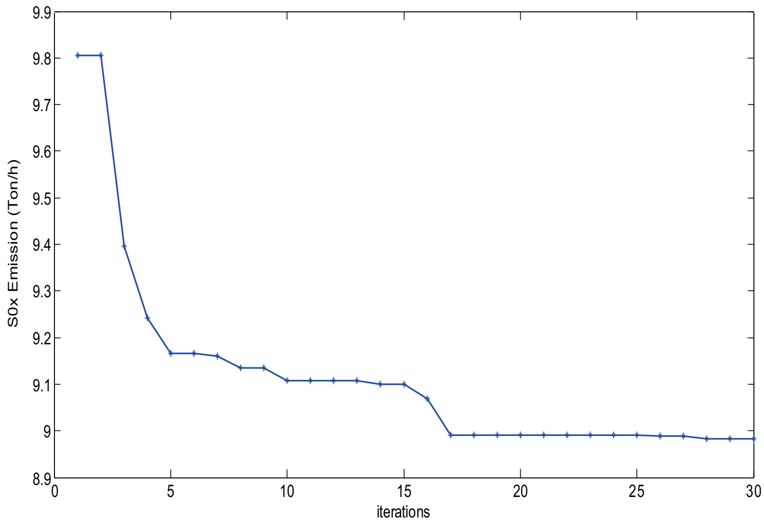

Fig. 3. Convergence characteristic for SO_2 emission minimization (3-unit system, demand 850 MW) .

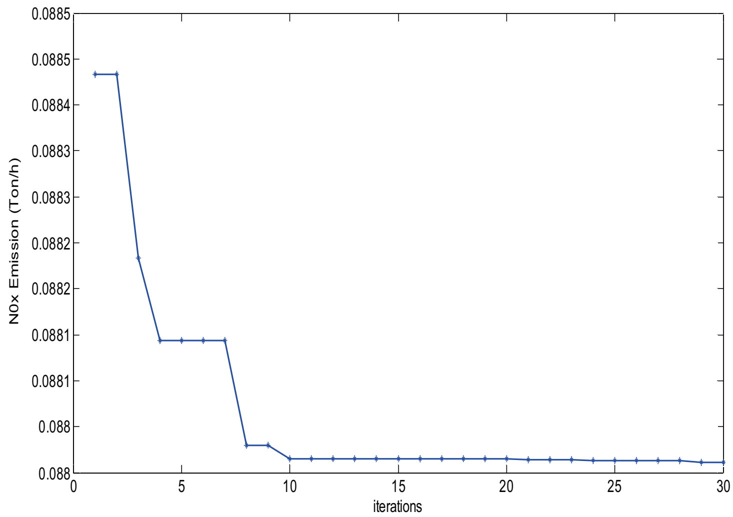

Fig. 4. Convergence characteristic for NO_x emission minimization (3-unit system, demand 850 MW) .

4.2. Test system 2

Test system the Algerian network with 114 bus, 15 generators for a load demand of 3727MW. With three cases, with valve point effect, without valve point effect and wind energy.The generators data are shown in Table 5 [17].

TABLE 5. GENERATORS PARAMETERS OF THE ALGERIAN ELECTRICAL NETWORK

	a_i	b_i	c_i	d_i	e_i	p_{Gi}^{min}	p_{Gi}^{max}
PG1	0.0085	1.50	0.0	130	0.0630	135	1350
PG2	0.0085	1.50	0.0	140	0.0980	135	1350
PG3	0.0170	2.50	0.0	0.0	0.0	10	100
PG4	0.0170	2.50	0.0	0.0	0.0	30	300
PG5	0.0085	1.50	0.0	0.0	0.0	135	1350
PG6	0.0170	2.50	0.0	0.0	0.0	34.5	345
PG7	0.0170	2.50	0.0	0.0	0.0	34.5	345
PG8	0.0170	2.50	0.0	0.0	0.0	34.5	345
PG9	0.0170	2.50	0.0	0.0	0.0	34.5	345
PG10	0.0170	2.50	0.0	0.0	0.0	30	300
PG11	0.0170	2.50	0.0	0.0	0.0	30	300
PG12	0.0030	2.00	0.0	0.0	0.0	60	600
PG13	0.0030	2.00	0.0	0.0	0.0	20	200
PG14	0.0170	2.50	0.0	0.0	0.0	10	100
PG15	0.0170	2.50	0.0	0.0	0.0	10	100

4.2.1. Case 1: quadratic fuel cost minimization (without valve point effect)

Tokens a glance on the application of the methods: PSO [17], AG [17] ,DE [17] ,GA [18] and ACO on the Algerian network with 114 bus, 15 generators summarized in the table 6 below :

TABLE 6. OPTIMIZATION RESULTS OF ACO APPROACH FOR 114-BUS

	PSO [17]	AG [17]	DE [17]	GA [18]	GA–DE–PS[18]	ACO
PG1	515.8825	515.11	462.3908	459.9665	455.9113	448.5994
PG 2	441.4111	241.9	459.5589	458.1525	455.9219	453.2352
PG 3	100.0000	99.9	99.9431	100.0000	100.0000	99.9999
PG 4	186.9059	135.07	192.5196	194.5837	194.3179	195.1008
PG 5	449.1401	674.04	453.0142	450.8240	448.7254	453.3391
PG 6	206.6362	163.76	196.6569	197.2413	196.0150	194.2377
PG 7	190.3105	211.16	189.0239	189.9870	190.8388	194.3792
PG 8	177.8684	277.06	193.9372	194.4170	197.8609	194.8601
PG 9	224.2734	228.37	192.1215	193.1359	193.7858	194.0982
PG 10	188.7075	182.49	188.1283	188.2248	190.9545	193.4037
PG 11	192.8819	153.95	189.0847	189.7243	191.9255	195.0039
PG 12	600.0000	598.41	599.9752	600.0000	600.0000	599.9998
PG 13	200.0000	197.54	199.9703	200.0000	200.0000	199.9999
PG 14	99.7997	98.11	99.9909	100.0000	100.0000	99.9999
PG 15	100.0000	39.46	99.9415	100.0000	100.0000	100.0000
Cost	**19235**	**19203**	**19203.34**	**19201.329**	**19199.444**	**19198.1447**
loss	87.9052	89.345	89.2570	89.2570	89.2570	89.3000
T	70	290	75	/	/	5.368

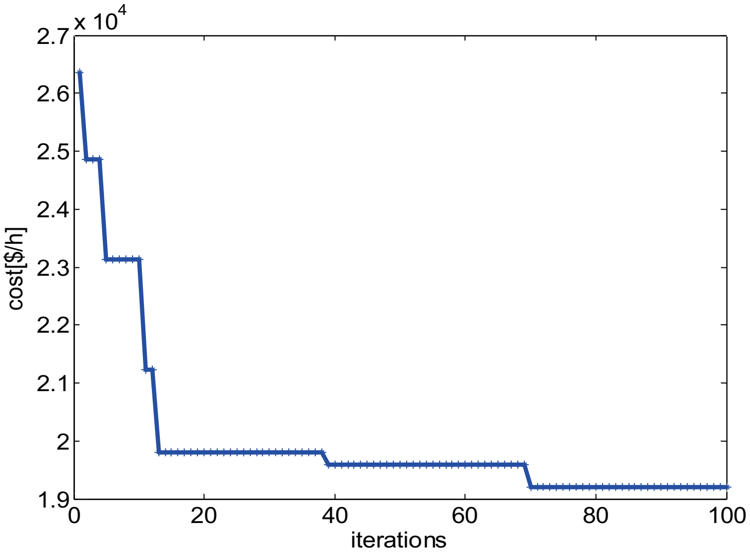

Fig. 5. The function cost values (without valve point effect) in different iterations for ACO method (114-bus 15 generator system).

This approch once again with an application on a network real watch which we can gain by exposing a cost of 19198.144738 $/h.

4.2.2. Case 2: quadratic fuel cost (with valve point effect)

Starting from table7, ACO approach is a remarkable method, it exceeds its two PSO and GA algorithms. the cost in the approch ACO is of 19668.944 $/h more reduced than the two other algorithms.

TABLE 7. COMPARISON RESULTS OF DIFFERENT METHODS FOR 114 BUS

	PSO	GA	ACO
PG 1	517.802884	486.133158	502.920051
PG 2	449.251316	452.058657	507.416702
PG 3	82.989616	98.971142	54.519066
PG 4	160.699043	262.000035	217.166413
PG 5	402.369380	462.762645	476.599114
PG 6	163.967158	175.270139	162.538877
PG 7	176.723179	110.311493	170.177094
PG 8	257.323265	177.141896	169.328588
PG 9	308.215313	202.679813	170.734154
PG 10	187.234247	237.412096	217.616865
PG 11	138.471784	196.742325	198.172433
PG 12	595.892975	577.398603	585.870470
PG 13	198.449760	193.592513	197.868268
PG 14	88.886657	92.923990	93.216973
PG 15	87.967166	89.296080	91.963181
Cost	**19880.225417**	**19707.709354**	**19668.944477**
Loss	89.2000	87.7000	89.1000
T	3.5898	6.368	5.9868

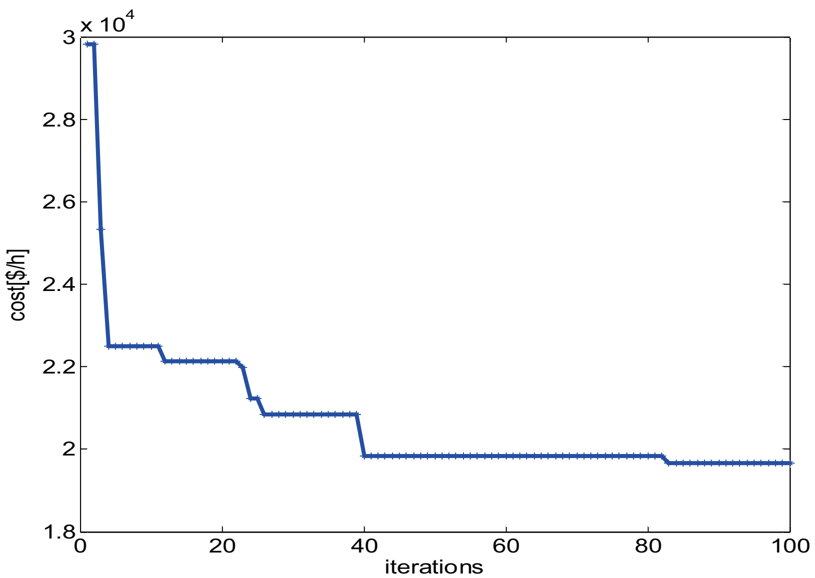

Fig. 6. The function cost values (with valve point effect) in different iterations for ACO method (114-bus 15 generator system).

4.2.3. Case 3: quadratic fuel cost minimization with wind energy

TABLE 8. TEST ACO WHEN WIND FARMS CONNECTED TO THE NETWORK WITH DIFFERENT RATES OF PENETRATION OF WIND POWER

	25%	**50%**	**75%**	**100%**
PG1	458.7262	451.2910	458.1683	466.7221
PG2	498.2000	460.4625	447.4511	466.3318
PG3	99.9621	99.9719	99.9985	100.0000
PG4	166.1502	182.3763	178.4471	168.7672
PG5	476.8023	470.1091	431.5938	467.8253
PG6	189.4932	188.3092	186.8376	185.0027
PG7	191.5243	163.9199	190.4132	183.4098
PG8	171.5142	185.5310	192.3008	170.4861
PG9	189.7868	190.0080	170.2114	179.7071
PG10	196.2460	186.7229	184.1267	168.1049
PG11	182.5051	187.5706	201.7174	159.9223
PG12	570.5276	599.9976	599.9965	599.9883
PG13	199.9705	200.0000	199.9939	199.9939
PG14	99.84772	99.9864	99.9999	99.99363
PG15	100.0000	99.9999	99.9997	100.0000
losses	89.3000	89.3000	89.3000	89.3000
Cost	**19132.4593**	**18770.31241**	**18535.7463**	**18356.3569**

When we have integrated renewable energy, namely wind energy, the cost has decreased, and this when we increase the percentage of its implication.

5. Conclusion

In this article we have applied a new approach ant colony algorithm (ACO). Proposed approach was tested on 3-unit and 15-unit systems. The obtained results were compared to those of other researchers. The results show clearly the robustness and efficiency of the proposed approach in term of precision and convergence time.

We note that the method is effective for the EPD in comparison with other methods (GA and PSO), and when the renewable energy (wind energy) has connected to the network, the cost has decreased, and this when we increase the percentage of its implication.

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